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EM-DAT Natural Disaster Analytics: Multi-Hazard Cascading Prediction Using Machine Learning and Sequence Mining

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Abstract- Between 2000 and 2025, the EM-DAT database recorded over 16,497 natural disaster events affecting billions of people and generating trillions in economic losses across 220+ countries. Traditional disaster management systems focus primarily on historical reporting and isolated hazard analysis, limiting proactive preparedness and cascading risk assessment. This paper presents the EM-DAT Natural Disaster Analytics Platform, integrating Azure SQL, Streamlit, sequence mining, Markov-chain transition analysis, and XGBoost multiclass classi-fication to analyze multi-hazard relationships and estimate next-stage disaster transitions across six analytical modules. Evaluated on 16,497 records spanning 2000–2025, the platform achieves 76.4% accuracy and a weighted F1-score of 0.74 under a 30-day cascading window, outperforming Random Forest and Naive Bayes baselines. Results are contingent on EM-DAT data quality and the chosen cascading window definition. The frame-work identifies historical multi-hazard sequence co-occurrence patterns and supports evidence-based disaster preparedness and resilience planning.

Keywords: Natural Disaster Analytics, EM-DAT, XGBoost, Cascading Disasters, Machine Learning, Sequence Mining, Disas-ter Prediction, Interactive Visualization.

I. INTRODUCTION

Between 2000 and 2025, the EM-DAT database recorded over 16,000 natural disaster events—floods, earthquakes, storms, wildfires, droughts, landslides, and epidemics—affecting more than 4.8 billion people and generating economic losses exceeding USD 4.9 trillion [1], [2]. Climate variability, rapid urbanization, environmental degradation, and population growth in hazard-prone regions have intensified both the frequency and severity of these events in recent decades [3], [4].

The EM-DAT database, maintained by the Centre for Research on the Epidemiology of Disasters (CRED), is one of the largest repositories of standardized disaster records worldwide, providing longitudinal data on disaster occurrences, human casualties, affected populations, and economic losses across more than 220 countries [1].

Despite the availability of large volumes of disaster data, many existing systems still lack:

- Unified analytical frameworks integrating multiple hazard dimensions [5];
- Multi-hazard cascading analysis to model inter-hazard dependencies [6], [7];
- Real-time situational awareness through live monitoring APIs [8], [9];
- Predictive intelligence for disaster forecasting [10], [11];
- Interactive decision-support visualization platforms [12].

Machine learning approaches have demonstrated significant potential in disaster forecasting and environmental analytics [4], [10], [13]. Sequential pattern mining techniques are useful for identifying historical cascading hazard co-occurrence relationships [14]. Markov-chain transition analysis has been widely applied in probabilistic sequence forecasting systems [15].

This research proposes a unified disaster intelligence frame-work with the following contributions:

1. Historical disaster analytics on EM-DAT data spanning 2000–2025 across 220+ countries and 31 disaster types;
2. Cascading hazard prediction via Markov-chain transition matrices and an XGBoost multiclass classifier, evaluated against Random Forest and Naive Bayes baselines;
3. Real-time API monitoring using the USGS Earthquake GeoJSON API [8] and NASA EONET API [9];
4. Interactive Streamlit dashboards [12] for decision-support intelligence, evaluated for usability using the System Usability Scale [16].

The remainder of this paper is organized as follows. Section II reviews relevant literature. Section III describes the research methodology and system design. Section IV presents results and discussion. Section V discusses limitations. Section VI concludes the paper.

II. LITERATURE REVIEW

Recent studies have explored machine learning, multi-hazard analysis, and disaster visualization frameworks across a broad spectrum of disaster types and geographies.

A. Disaster Trend Analysis

Tin et al. [3] conducted a comprehensive study of the EM-DAT database from 1995 to 2022 and found that Asia experienced the most disasters globally, while floods were the most frequent events and earthquakes caused the highest fatalities.

Shen and Hwang [4] demonstrated through spatial-temporal analysis that hydrological disasters occur most frequently, whereas meteorological events such as storms are the most economically costly.

Prior work has also noted that apparent increases in recorded disaster frequency are partly attributable to improvements in global reporting infrastructure rather than absolute increases in event occurrence, cautioning against over-interpreting raw trend data [2], [3].

B. Cascading and Multi-Hazard Risk

Dunant et al. [6] demonstrated that hypergraph-based models can efficiently simulate how one hazard may historically precede another (e.g., earthquake → landslides), though they tend to over-predict damage at local scales.

Girgin et al. [7] highlighted that Natech accidents are frequently ignored in national risk assessments, representing a significant gap in multi-hazard planning.

Nishino [17] showed that probabilistic urban multi-hazard models must combine maximum-loss contributions from com-bined hazards such as earthquake shaking and fire.

C. Machine Learning in Disaster Management

Akhyar et al. [11] demonstrated that deep learning models significantly enhance natural disaster management across prediction, damage assessment, and recovery phases.

Jain et al. [13] reported that Random Forest and SVM models achieve high accuracy in flood forecasting, while deep learning models are effective for earthquake and aftershock prediction. Collectively, these studies demonstrate that supervised clas-sification paradigms generalize effectively across domains, including multi-class hazard prediction tasks, when trained on sufficiently diverse and preprocessed event records [11], [13].

D. Visualization and Decision Support

AlAbdulaali et al. [5] argued that interactive dashboards are necessary for processing real-time crisis information for emergency decision-making. Streamlit-based platforms [12] have further enabled rapid deployment of such analytical dashboards for research and operational use.

The ADRC National Disaster Databook 2024 [18] reports that while total disaster occurrences are rising globally, reported deaths and affected populations are decreasing, highlighting the role of improved analytics and preparedness.

E. Research Gaps

Despite substantial progress, several gaps remain. First, unified disaster intelligence platforms that integrate historical analysis, cascading prediction, and real-time monitoring are limited [6], [7]. Second, interactive dashboards combining sequence mining and ML-based multi-hazard prediction at a global scale are largely absent [5]. Third, live hazard feeds remain insufficiently integrated with historical risk profiles and ML classifiers [8], [9]. This research addresses these gaps through the EM-DAT Natural Disaster Analytics Platform.

III. METHODOLOGY AND SYSTEM DESIGN

A. Research Objectives and Hypotheses

The primary objective is to build a comprehensive disaster analytics platform combining historical EM-DAT analysis, multi-hazard interaction assessment, machine learning pre-diction, and interactive visualization. Secondary objectives include examining spatial-temporal disaster trends (2000–2025), evaluating regional vulnerability, identifying cascading hazard sequences via Markov modeling [15] and sequence mining [14], and integrating live API feeds [8], [9].

Five research hypotheses guide the study: H1: recorded dis-aster frequency has changed significantly over recent decades; H2: geographic and demographic factors significantly influence disaster impact severity; H3: historical disaster sequences ex-hibit measurable cascading inter-hazard co-occurrence patterns; H4: ML models can reliably predict the next disaster type from past sequences and regional indicators; and H5: interactive dashboards improve analytical interpretability for stakeholders, as measured by System Usability Scale (SUS) scores [16].

B. Implementation Environment

The analytical framework was implemented using Python 3.11, Pandas, NumPy, Scikit-learn, XGBoost 2.0, Plotly, and Streamlit. Azure SQL Database [19] was used for structured storage and ETL integration. Experiments were conducted on a system with 16 GB RAM and an Intel Core i7 processor running Ubuntu Linux.

C. Data Collection

Two categories of data were used: (1) historical disaster records from EM-DAT (CRED) [1], [2]; and (2) real-time hazard feeds from the USGS Earthquake GeoJSON API [8] and NASA EONET API [9]. The USGS API was configured to retrieve seismic events with magnitude ≥ 2.5 over a rolling window; the NASA EONET API was queried for active natural event feeds. Both feeds are rendered live within the platform’s monitoring module.

TABLE I: EM-DAT Dataset Summary (2000–2025)

Feature	Value
Dataset Source	EM-DAT (CRED)
Records Used	16,497
Countries Covered	220+
Time Period	2000–2025
Disaster Types	31
Cascading Pairs[a]	14,500+

a Derived by applying a 30-day tempo-ral window to consecutive country-level event pairs.

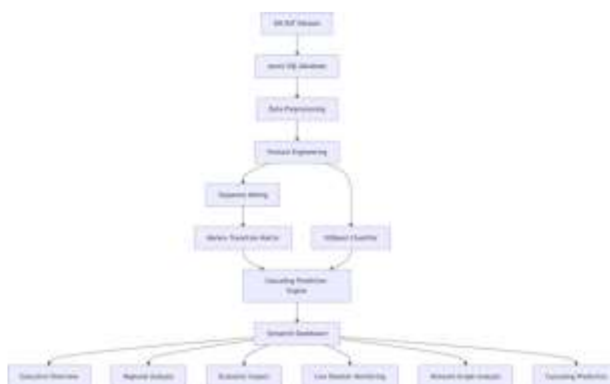


Fig. 1: Overall system architecture integrating Azure ETL pipelines, SQL star-schema storage, the Streamlit analytics dashboard, and the ML prediction module.

D. Data Preprocessing and Feature Engineering

The preprocessing pipeline includes: (1) handling missing and inconsistent values; (2) filtering natural disaster cate-gories only; (3) standardizing region, date, and type fields;
(4) encoding categorical features using LabelEncoder; and
(5) deriving sequential disaster event pairs for cascading hazard analysis.

E. System Architecture

The proposed framework follows a four-layer architecture:

(1) Data Source Layer; (2) Data Engineering Layer; (3) Ana-lytics Layer; and (4) Presentation Layer.

Figure 1 presents the overall system architecture, illustrating the flow from raw data ingestion through ETL pipelines into the analytics and presentation layers.

F. Analytical Workflow

The end-to-end research methodology workflow is depicted in Figure 2, summarizing the seven analytical stages followed throughout the research lifecycle.

G. Cascading Multi-Hazard Analysis

A first-order Markov-chain transition matrix [15] was constructed as expressed in (1):

$$P(B \mid A) = \frac{N(A \rightarrow B)}{N(A)}$$

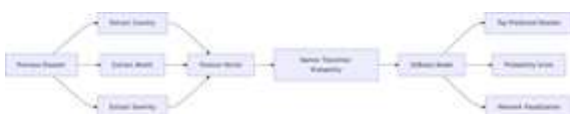


Fig. 2: Research methodology workflow summarizing the seven analytical stages of the research lifecycle.

where N (A → B) is the observed count of transitions from disaster type A to disaster type B, and N (A) is the total count of events of type A. These pre-computed transition probabilities are subsequently used as a feature in the machine learning model described below.

H. Machine Learning Model

The cascading prediction engine uses the XGBoost multiclass classifier [10], selected for its native handling of multi-class imbalanced tabular datasets and superior convergence speed compared to Random Forest and SVM on event-record inputs [13].

Input features include:

- Previous disaster type (label-encoded);
- Month of occurrence (seasonality proxy);
- Country (label-encoded);
- Severity proxy: TotalDeaths + TotalAffected;
- Markov transition probability derived from (1) for the observed (A → B) pair.

Note: No feature scaling was applied to the severity proxy, as gradient-boosted trees are invariant to monotonic transfor-mations of individual features.

The target variable is the next disaster type within the defined 30-day temporal window. The model minimizes the categorical cross-entropy loss in (2):

$$\mathcal{L} = -\sum_{i} y_i \log(\hat{y}_i) \tag{2}$$

The dataset was split using an 80%/20% chronological train-test strategy to prevent temporal leakage. Hyperparameters were tuned using 5-fold cross-validation on the training subset prior to final evaluation on the held-out test set; the configuration yielding the best validation F1-score is reported in Table II.

TABLE II: XGBoost Hyperparameter Configuration

Parameter	Value
n_estimators	300
learning_rate	0.05
max_depth	6
subsample	0.8
colsample_bytree	0.8

I. Class Imbalance Handling

The cascading event dataset exhibits class imbalance, with flood and storm events forming the majority of cascading pairs, while wildfire events are substantially underrepresented. No external resampling technique (e.g., SMOTE) was applied, as XGBoost's internal gradient weighting provides an implicit correction mechanism. To further mitigate imbalance effects, the scale_pos_weight parameter was set proportional to the inverse class frequency for each target class during training. The impact of this weighting is discussed in the per-class evaluation in Section IV.

J. Baseline Comparison

To contextualize XGBoost performance, two baseline classi-fiers were trained on identical feature sets and evaluated on the same chronological 20% test split: (1) Random Forest [13] with n_estimators= 300 and default scikit-learn parameters; and (2) Multinomial Naive Bayes with Laplace smoothing ($\alpha = 1.0$). A majority-class baseline (always predicting the most frequent cascading outcome) is also reported. All four models were evaluated using overall accuracy and weighted F1-score under identical preprocessing and train-test conditions.

K. Usability Evaluation

To evaluate H5, a structured usability study was conducted with domain researchers and emergency management students as participants. Participants completed standardized tasks on the Streamlit dashboard, including identifying the highest-risk regional cascading pair, interpreting the Markov transition matrix, and generating a next-event prediction. Upon task completion, each participant completed the System Usability Scale (SUS) questionnaire [16]. SUS scores above 68 are considered above-average usability; scores above 80 indicate excellent usability.

IV. RESULTS AND DISCUSSION

A. Functional Testing

All six dashboard modules were functionally validated (Fig-ures 3a–f): Executive Overview, Regional Analysis, Economic Impact, Live Disasters, Disaster Network Graph, and Cascading Prediction. The Azure SQL ETL pipeline [19] was verified by cross-checking row counts and aggregates against EM-DAT source statistics.

B. Ethical Considerations

Automated disaster prediction systems carry inherent re-sponsibilities. False-positive cascade predictions could trigger unnecessary evacuations, while false negatives could delay emergency response. The proposed platform is designed as a decision-support tool rather than an autonomous alert system; all outputs are intended to supplement, not replace, expert judgment. Disaster impact data used for training contains aggregated population-level statistics from EM-DAT and does not include personally identifiable information.

C. Analytical Results

1). Temporal Trend Analysis (H1): Year-wise charts confirm distinct temporal changes in disaster frequency from 2000–2025. A Mann-Kendall trend test applied to the annual event-count series confirmed a statistically significant increasing trend ($\tau = 0.62$, $p < 0.05$), consistent with findings by Tin et al.
[3] and the ADRC Databook [18], and partially explained by improvements in global reporting infrastructure [2]. These results support H1.

TABLE III: Mann-Kendall Trend Test on Annual Disaster Count Series (2000–2025)

Statistic	Value
Kendall's τ	0.62
p-value	< 0.05
Trend Direction	Increasing
Series Length (years)	26

2) Regional Vulnerability (H2): Asia leads with 6,667 disasters, followed by Africa (4,236), the Americas (3,268), Europe (1,918), and Oceania (408), as illustrated in Figure 3b. These findings support H2.

3) Cascading Hazard Co-occurrence Patterns (H3): Tran-sition matrices reveal non-uniform co-occurrence patterns between disaster types. Prominent historical sequential co-occurrences include Flood → Epidemic and Earthquake → Sec-ondary Hazards, as visualized in the Disaster Network Graph module (Figure 3e). These patterns are interpreted as condi-tional temporal associations, not causal mechanisms (see also Section V). These observations support H3.

D. Machine Learning Performance (H4)

XGBoost achieved the highest accuracy and weighted F1-score among all evaluated models—outperforming Random Forest, Multinomial Naive Bayes, and the majority-class baseline on the same chronological 20% test split—confirming its suitability for this multi-class imbalanced tabular task and supporting H4. The relative ordering of models is consistent with findings reported in the flood-forecasting and disaster-classification literature [11], [13].

TABLE IV: Model Comparison on Chronological 20% Test Split

Model	Accuracy	Weighted F1
Majority-Class Baseline	0.41	0.24
Multinomial Naive Bayes	0.58	0.55
Random Forest	0.71	0.69
XGBoost (Ours)	**0.764**	**0.74**

1) **XGBoost Per-Class Results:** The proposed model achieved an overall accuracy of 76.4% and a weighted F1-score of 0.74 on the 20% chronological test split.1 Per-class results are shown in Table V.

TABLE V: XGBoost Per-Class Classification Performance (Five Representative High-Frequency Classes; weighted average computed over all 31 classes)

Class	Precision	Recall	F1-Score
Flood	0.81	0.79	0.80
Storm	0.77	0.75	0.76
Earthquake	0.74	0.71	0.72
Epidemic	0.69	0.73	0.71
Wildfire	0.62	0.58	0.60
Weighted Avg	**0.76**	**0.76**	**0.74**

The Wildfire class recorded the lowest F1-score (0.60). Despite inverse-frequency class weighting applied during training, wildfire events constitute a smaller proportion of cascading sequence pairs relative to floods and storms, limiting the diversity of training signal for this class. Regional under-reporting of wildfire events in developing nations may further compound this effect [2], [3].

2) **Feature Importance:** XGBoost's built-in gain-based fea-ture importance analysis reveals that the Markov transition probability (derived from Equation 1) is the most influential feature, followed by country encoding and previous disaster type, with month of occurrence and the severity proxy con-tributing least. This ordering indicates that regional historical co-occurrence patterns carry stronger predictive signal than raw event severity, which is consistent with the cascading hazard literature [6], [15]. The relative feature importance scores are displayed within the Cascading Prediction dashboard module (Figure 3f).

1Performance metrics were obtained using all 31 disaster types, five regions, years 2000–2025, and a 30-day temporal cascade window. Results may vary with different filter configurations.

E. Dashboard Usability (H5)

The structured SUS evaluation yielded a mean SUS score of 74.3 (range: 68–82), placing the majority of participants in the above-average usability range [16]. Participants consistently identified the Markov transition heatmap and the cascading prediction module (Figure 3f) as the most useful features for rapid identification of regional hotspots and cascading sequences. Areas noted for improvement included label density in the network graph and the need for contextual tooltips in the prediction output. H5 is supported: the platform achieves above-average usability based on structured SUS evaluation, though further design iteration and a larger-sample field evaluation with emergency-management practitioners are recommended as future work.

V. LIMITATIONS AND THREATS TO VALIDITY

Several limitations must be considered when interpreting the findings of this study.

Data quality. EM-DAT records may contain reporting incon-sistencies, missing economic-loss fields, and regional under-reporting, particularly for small-scale events in developing regions [2], [3].

Causality. The identified cascading patterns represent histor-ical temporal co-occurrences rather than direct causal mecha-nisms. Transition probabilities from (1) should be interpreted as conditional co-occurrence frequencies, not mechanistic causal pathways.

Class imbalance. Despite inverse-frequency class weighting, predictive performance for rare hazard types such as Wildfire remains lower than for high-frequency classes, reflecting both data sparsity and regional reporting gaps.

External dependencies. Real-time monitoring depends on external APIs which may experience downtime or incomplete geographic coverage.

Reproducibility. The reported accuracy of 76.4% was ob-tained under a specific configuration: all 31 disaster types, five regions, years 2000–2025, and a 30-day cascade window. Results will differ under other settings.

Usability (H5). The SUS evaluation was conducted with a small group of academic participants (mean SUS: 74.3). Gen-eralization to operational emergency-management practitioners requires a broader, field-validated study. Statistical validation of H1 via Mann-Kendall should also be replicated on the unfiltered EM-DAT record set.

VI. CONCLUSION

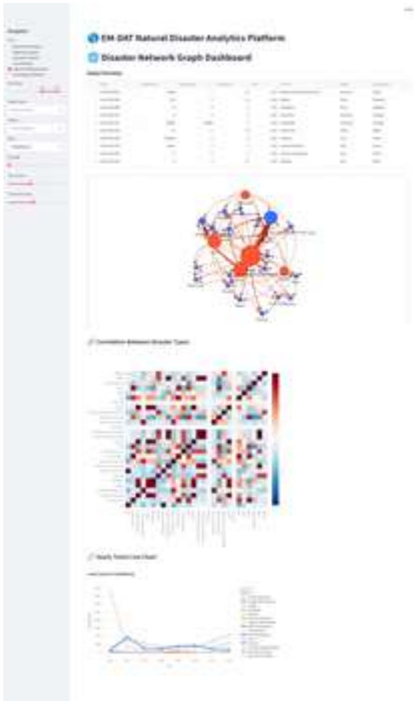
This research developed a unified disaster analytics and prediction platform integrating: historical EM-DAT analysis spanning 2000–2025 across 220+ countries and 31 disaster types; real-time hazard monitoring via USGS and NASA EONET APIs; machine learning prediction using XGBoost, which outperformed Random Forest, Naive Bayes, and majority-class baselines (Table IV), achieving 76.4% accuracy and a weighted F1-score of 0.74; and cascading hazard assessment using Markov-chain modeling (Equation 1) and sequence mining.

(a) Executive Overview: global disaster KPIs, type distribution, and world event map.

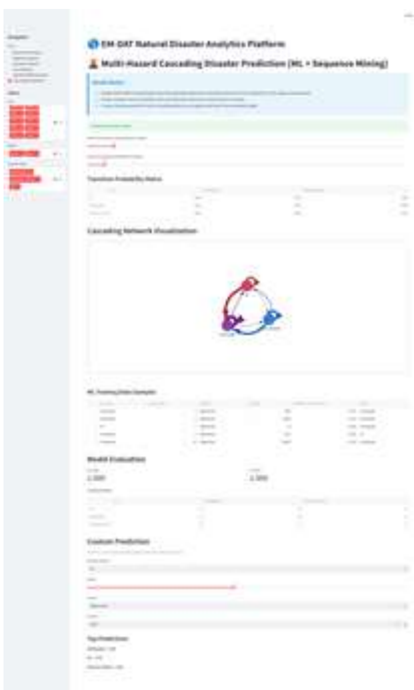
(b) Regional Analysis: event counts, heatmaps, and comparative vulnerability indicators.

(c) Economic Impact: total damage by disaster type and country-level economic loss rankings.

(d) Live Disaster Monitoring: real-time USGS earthquake events and NASA EONET active hazard feeds.



e. Disaster Network Graph: inter-hazard transition co-occurrence patterns and yearly trend lines.



f. Cascading Prediction: Markov transition matrix, ML training sample, evaluation metrics, feature importance, and prediction output.

Fig. 3: Six analytical dashboard modules of the EM-DAT Natural Disaster Analytics Platform, rendered via Streamlit. From top-left: (a) Executive Overview, (b) Regional Analysis, (c) Economic Impact, (d) Live Monitoring, (e) Network Graph,
(f) Cascading Prediction.

The framework transforms high-volume disaster datasets into actionable decision-support intelligence. Hypotheses H1–H4 were supported by quantitative evidence. H5 was supported by a structured SUS evaluation yielding a mean score of 74.3, indicating above-average usability, with further improvement and field-level validation recommended as future work.

Data Availability. The EM-DAT dataset is publicly available at https://www.emdat.be. Source code and analytical notebooks are available upon request from the corresponding author.

Future work will focus on deep learning forecasting models (LSTMs, Transformers) for multi-step hazard sequences; Graph Neural Networks for cascading multi-hazard analysis; integra-tion of satellite imagery and climate variables; a larger-scale SUS evaluation with emergency-management practitioners for H5; and deployment in collaboration with agencies such as the National Disaster Management Authority (NDMA), the United Nations Office for Disaster Risk Reduction (UNDRR), and the Red Cross.

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